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Prediction of Defect Propensity for the Manual Assembly of Automotive Electrical Connectors

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Abstract
Assembly for automotive production represents a significant proportion of total manufacturing cost, manufacturing time, and overall product cost. Humans remain a cost effective solution to adapt to the requirements of increasing product complexity and variety present in today's flexible manufacturing systems. The human element present in the manufacturing system necessitates a better understanding of the human role in manufacturing complexity. Presented herein is a framework for enumerating assembly variables correlated with the potential for quality defect, presented in the design, process, and human factors domain. A case study is offered that illustrates on a manual assembly process the effect that complexity variables have on assembly quality.

Keywords: Manual Assembly, Complexity Model, Quality

1 Introduction

Comprising many diverse and critical processes, automotive manufacturing industries have continually become more complex due to decreasing product life cycles and increased demand for quality and product variety. Assembly which represents a significant portion of automotive manufacturing and the production process greatly contributes to the final product cost and quality. An example of this is the BMW 7 Series, where the projected number of variants of this single product line has been found to be 10^{17} (BMW Group, 2013). Modern assembly line's increasing complexity and variety has created corollary complexity in the manufacturing environment which introduces additional assembly defect potential but has also driven better understanding and control of assembly quality. The intent of this work is to further that understanding for a class of manually-assembled interfaces.

Comprising on average 40% of product cost and up to 50% of total manufacturing cost, assembly activities can be seen as very costly and time intensive (Röhrdanz 1997; Bi et al. 2007). Having such a large influence on the cost of a product, it is clear how imperative the reduction of defects is to the success of an assembled product. In automotive assembly this influence is clearly evident from the

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knowledge that single defects can result in the loss of thousands of dollars through delayed rework, scrapping of entire vehicles, or recall.

Brand quality is a key factor in the automotive marketplace when a customer is making a purchasing decision. During this decision, a customer will indirectly research the defect rates of vehicles by consulting databases such as J.D. Powers. The integrity of electrical connectors, fit and finish of the vehicle body, and final paint quality are some of the most highlighted defect categories due to being easily evaluated by the customer themselves during the purchase and through their use of the product. Easily accessible defect data has driven automotive manufacturers to continually increase their internal quality initiatives and adopt new practices in the mitigation of assembly defects. This is especially true in manual assembly where Su et al. (2010), Shibata (2002), and Vineyard (1999) found that up to 40% of total defects resulted from operator error and that these defects are not always obvious.

Research into defining strategies for characterizing assembly complexity has shown a relationship with final product quality. Key assembly complexity models have previously been successfully applied to such markets as home audio and office copier production.

1.1 Hinckley Model

Hinckley (2003), whose data was based on semiconductor products, found that defect per unit (DPU) was positively correlated with total assembly time and negatively correlated with the number of assembly operations. He defined an assembly complexity factor as:

$$C_f = TAT - t_0 \times TOP \tag{1}$$

Where,
TAT = Total assembly time for the entire product
t_0 = Threshold assembly time
TOP = Total number of assembly operations

In order to calibrate the relationship between the total assembly time and the total number of assembly operations the threshold assembly time was included in the complexity factor and was defined as the time required to perform the simplest assembly operations. Hinckley showed that the complexity factor and defect rate showed a positive linear correlation on a log-log scale or:

$$\log DPU = k \times \log C_f - \log C \tag{2}$$

$$DPU = \frac{(C_f)^k}{C} \tag{3}$$

Where, C and k are constants

1.2 Shibata Model

Shibata (2002) applied the Hinckley model to the assembly of Sony's compact disc players but found that the Hinckley model did not consider assembly design factors nor could it evaluate a specific workstation in a larger assembly line. He proposed that a prediction model centered on process and design based complexity at the workstation level could improve on the earlier work. Shibata also used Sony standard time, a well-known estimation of the standard processing time for electronics, to determine assembly time. Similar to the Hinckley model, the process based complexity factor (Cf_{Pi}) was defined as:

$$Cf_{Pi} = \sum_{j=1}^{N_{ai}} SST_{ij} - t_0 \times N_{ai} \tag{4}$$

Where,
SST_{ij} = Time spent on job element j in workstation i
t_0 = Threshold assembly time
N_{ai} = Number of job elements in workstation i

Shibata derived a similar correlation between the process based complexity factor and DPU (5) on a log-log scale:

$$\log DPU_i = K \times \log Cf_{Pi} - \log C \tag{5}$$

$$DPU_i = \frac{(Cf_{Pi})^K}{C} \tag{6}$$

Where, C and K are constants

Shibata than derived a design based complexity factor (7) and correlated it and DPU (8-9) on a log-log scale:

$$Cf_{Di} = \frac{K_D}{D_i} \tag{7}$$

$$\log DPU_i = b \times \log Cf_{Di} - \log a \tag{8}$$

$$DPU_i = a \times (Cf_{Pi})^b \tag{9}$$

Where,
K_D = Arbitrary coefficient for calibration with process based complexity
D_i = Ease of assembly of workstation i
a and b are constants

According to Mendenhall and Sincich (1995), adding independent variables to the regression function will help to improve the accuracy and stability. Using this, Shibata derived a bivariate prediction model by combining (5) and (8):

$$\log DPU_i = k_1 \times \log Cf_{Pi} + k_2 \times \log Cf_{Di} + C \tag{10}$$

1.3 Su, Liu, and Whitney Model

Su, Liu, and Whitney (2010) applied the Shibata model to copier assembly and found the Shibata model was not appropriate for larger electromechanical products. Su reported the R-squared value to be only 0.257 when using the Shibata model. Su et al. (2009) partially improved on the Shibata model for copiers by using Fuji Xerox Standard Time which was more suited to copier assembly than Sony Standard Time. Su's method also utilized Ben-Arieh's (1993) fuzzy expert system approach for analyzing difficulty of assembly combined with the analytic hierarchy process (AHP) and was able to achieve an R-squared value of 0.793 in the evaluation of three copier assembly products.

1.4 Antani Model

Antani (2014) built on the Hinckley, Shibata, and Su models by redefining manufacturing complexity as a measure of the impact of design, process, and human factor variability on assembly. It is the first model to include human factors with design and process variables as one comprehensive measure of manufacturing complexity (Antani 2014). The generalized complexity model for defect rate (DPMO, defects per million opportunities) was empirically defined by Antani as:

$$DPMO = k_0 + \left[C_d C_p C_h\right] \cdot \begin{bmatrix} k_1 \\ k_2 \\ k_3 \end{bmatrix} \tag{11}$$

Where,
k_0 = Empirical process constant
C_d = Coefficient of design complexity
C_p = Coefficient of process complexity
C_h = Coefficient of human factors complexity
$k_{1,2,3}$ = Empirical constants

Antani categorized the key input variables under each coefficient by dividing the three sources of variability into three separate subcomponents. The key input variables were derived through literature review in the areas of each source variability and observation in a manufacturing environment. The complexity factors were defined as:

$$C_d = \pm\alpha_1 D_{fd} \pm \alpha_2 D_{ad} \pm \alpha_3 D_{ac} \pm \alpha_4 D_{mc} \tag{12}$$

Where,
$\alpha_{1\ldots n}$ = Empirical constants
D_{fd} = Feature design variable
D_{ad} = Assembly design variable
D_{ac} = Component design variable
D_{mc} = Material design variable

$$C_p = \pm\beta_1 P_{tf} \pm \beta_2 P_{as} \pm \beta_3 P_{nt} \pm \beta_4 P_{tu} \pm \beta_5 P_{vt} \tag{13}$$

Where,
$\beta_{1\ldots n}$ = Empirical constants
P_{tf} = Tooling/Fixture design variable
P_{as} = Assembly sequence variable
P_{nt} = Number of tasks in takt variable
P_{tu} = Assembly takt utilization variable
P_{vt} = Assembly time variation variable

$$C_h = \pm\gamma_1 H_{ef} \pm \gamma_2 H_{tr} \pm \gamma_3 H_{cl} \pm \gamma_4 H_{we} \tag{14}$$

Where,
$\gamma_{1\ldots n}$ = Empirical constants
D_{fd} = Feature design variable
D_{ad} = Assembly design variable

D_{ac} = Component design variable
D_{mc} = Material design variable

Figure 1 outlines the input variables for the Assembly Design (D_{ad}) variable category of the design driven complexity factor (C_d) as was defined by Antani.

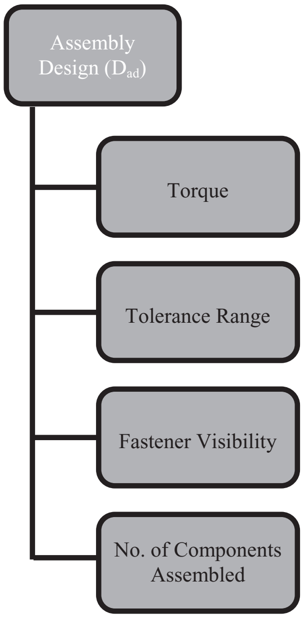

Figure 1: Adapted from Antani (2014) assembly design variables

Antani observed 46 mechanical fastening processes over a one year time span, to eliminate production outliers, and developed a regression-based predictive model to predict defects in a fully automated and semi-automated automotive assembly process. He validated the model using three case studies, two highlighting quality improvements and one automated process where the human factors coefficient played no role, and found the actual vs predicted defect rate in each case to be highly correlated, with an R-squared value for the developed model of 0.919. Antani demonstrated the potential of the model as a design and optimization tool to evaluate the design, process, and human factors on product quality prior to entering real-world assembly, and as a process improvement tool.

2 Methodology

The methodology used in this research adapts the methods developed by Antani (2014) for use with electromechanical connections in a large complex system. Antani's model has previously been successfully validated against both fully-automated and semi-automated mechanical fastening processes. The research presented herein seeks to use a fully manual automotive electrical connector assembly process to further validate the predictive model methodology and introduces the concept of electrical signal continuity as a factor of quality.

2.1 Complexity Input Variable Ideation

Following the method described by Antani, the correlation between defect rate and complexity can be written as in equation (11). Due to variation in the design principles and manufacturing of mechanical fasteners and automotive electrical connectors, a new table of input variables was created. Due to the high variability and lack of substantial research into defining the relationship between complexity for fully manual assembly processes and defect rates, another goal of this initial study was to determine which key input variables had the most significant impact on the electrical connector regression model and reduce future data collection requirements as certain variables require a line stoppage to collect.

The sources of the complexity variables presented in this work were derived from literature, input from technical staff and production workers, and performing process connections on training simulators. The complete list of input predictor variables can be found below.

Class	**Variable**
Feature Design	Engagement length
	Connector width
	Connector height
	Number of conductors
	Lever direction
	Locking feature
	Sealing mechanism type
	Pigtail length (female)
	Pigtail length (male)
	Pin Style
	Surrounding color
	Male color
	Female color
Assembly Design	Engagement force
	Number of fixed ends
	Harness breakout direction (Bend angle)
	Verification operation
	Connector orientation
	Visible vs. Blind
	Connector in confined space

Table 1: Product design electrical connector input variables

Class	**Variable**
Tooling / Fixture Design	Assistance tooling?
	Are gloves required?
Assembly Sequence	Sequential requirement
	Part install immediately followed by connect?
	Where is defect caught?
	Where is defect corrected?
Takt information	Number of connections per takt
	Total tasks in takt
	Tasks at 100%
	Utilization of takt

	Utilization variation of takt (options) High
	Utilization variation of takt (options) Low
	Number of extra option tasks in takt
	BVIS notification of connection

Table 2: Process electrical connector input variable

Class	**Variable**
Ergonomics	Work height
	Sitting/standing
Cognitive Load	Finding connectors
	Verification mark/feedback
Work Environment	Stability of work base
	Presentation of vehicle
	Lighting

Table 3: Human factors electrical connector input variables

2.2 Data Collection

The chosen process of human assembly of automotive electrical connectors was found to be the second-most common source of automotive assembly defects by Antani (2014) based on his historical analysis of assembly defects over a one-year analysis of automotive production data. Also knowing that consumers use J.D. Power's easily accessible vehicle electrical connector defect data during their purchasing decision, the human assembly of automotive electrical connectors was chosen and carried out in an automotive assembly plant in South Carolina, USA.

Due to the complex and highly variable nature of human assembly (Townsend & Urbanic 2015), a strong emphasis was placed on the formation and subsequent collection of the input variables. Through literature and process investigation, 41 input variables were collected for 9 electrical connectors. The electrical connectors used in this study were highlighted due to their historic defect rate so that a representative sample of both high and low rates were represented and evaluated using a single tool. Defect data and input variable information was gathered for six months' worth of vehicle production to limit the influence of production outliers on the results of the regression model.

3 Results

Minitab was employed to analyze the 41 input variables and defect rates which were recorded for the 9 electrical connectors. The statistical model was generated by using the input variables as both continuous and categorical predictor variables and the defect rate as the response variable.

3.1 Analysis of Predictor Variables

To better understand the relationship between the individual predictor variables and defect rate, fitted line plots were applied to determine their respective correlations or R-squared. The plots gave an indication whether a higher order fit would significantly benefit the final regression model. A lower order fit for each predictor variable was desired in order to eliminate the added complexity to the final regression model that higher order coefficients produce. The R-squared and R-squared (adj.) for each variable was calculated at a linear, quadratic, and cubic fit level. Figure 2 below represents the largest increase in fit from all variables analyzed. As seen in Figure 2(a), the linear fit has an R-squared of 0.847 and increases from the cubic fit in Figure 2(b) to 0.899 which also accumulates two additional terms and a higher order to the final model. The analysis of the input variables is a very important step that provides a better understanding of the relationships that are occurring within the predictive model. Additional Analysis of Variance (ANOVA) provides the p-values for each predictor variable and assists in determining the appropriateness of rejecting the null hypotheses in a hypothesis test. A p-value less than the standard alpha of 0.05 would statistically corroborate that the variable has a significant effect on the response variable. Continued analysis of the variables through an ANOVA analysis is planned to provide a supplementary understanding of the input predictor variables as well as statistically aid in the pre-model and final selection of key impact variables to include in the regression model.

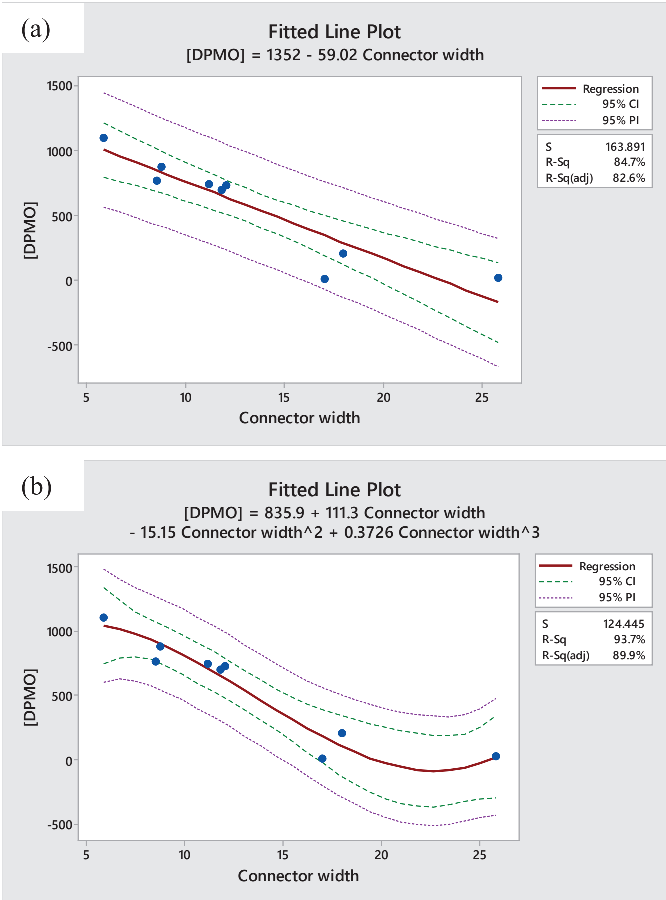

Figure 2: (a) Linear fit DPMO vs connector width, (b) Cubic fit DPMO vs connector width

3.2 Regression Model Building

Ordinary Least Squares (OLS) regression was conducted to model the relationship between the response variable defect rate (DPMO) and the input predictor variables, as demonstrated by Antani. OLS estimates the equation by determining the minimum sum of the squared distances between the sample's data points and the predicted values. Using the knowledge gained through the analysis of the input predictor variables, an initial model was built using OLS and can be found in Figure 3 below. The initial model achieved an R-squared of 0.576 when comparing predicted vs actual defect rate (DPMO) through the use of a linear fit line passing through the origin. A linear fit line was used to assess how well the predicted vs actual defect rates align since a 100 percent accurate predictive model should display an R-squared value of 1 as well as a fit line coefficient in the linear equation $y(predicted\ DPMO) = a \times x(actual\ DPMO)$ of $a = 1$.

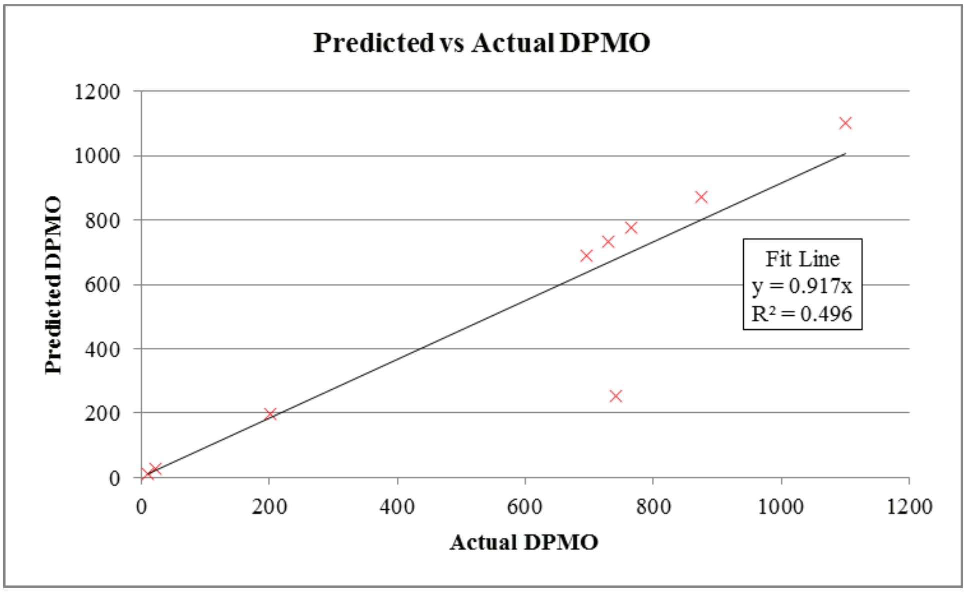

Figure 3: Regression model iteration 1

To improve the model, best subsets analysis was conducted to increase the R-squared value by cutting down on the number of variables used in the regression analysis. Best subsets analysis allows the projected predictability, precision, bias, and variability to be computed for each possible combination of variables in the model. This information will generate the best fitting regression model for the predictor and response variables provided.

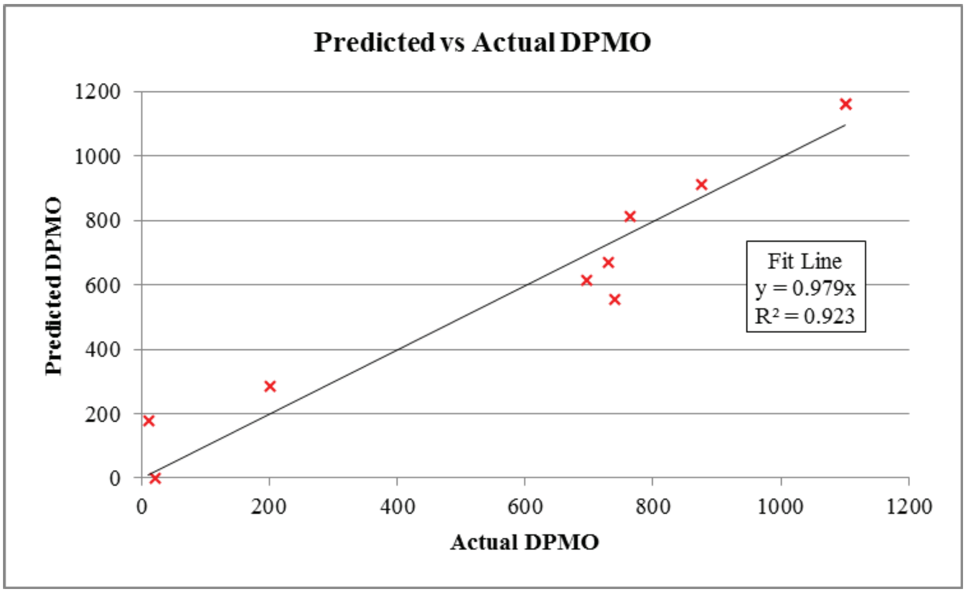

Figure 4: Regression model best subsets iteration

Through best subsets analysis, the model was able to be cut down from 41 input variables used in the first iteration to 6 input variables in the best fitting best subsets regression model. The reduction of variables coincided with an increase in the R-squared value to 0.923 as seen in Figure 4. This was the model with the highest R-squared value found through the best subsets analysis.

Variable	P-Value
Connector width	0.078
Engagement length	0.439
Connector height	0.457
Work Height	0.775
Female Pigtail	0.792
Male Pigtail	0.982

Table 4: P-values for best subsets variables.

The reduction in input variables drastically reduced the data collection requirements for continued validation against additional manual electrical connector processes not currently included in the model. Additional connectors are needed for validation of the model to assess whether the model is capable of predicting more than the connectors used to build the model and has applicability to further automotive electrical connector assembly processes.

The six variables included in the best subsets model were:

- Engagement length
- Connector width
- Connector height
- Work height
- Female pigtail
- Male pigtail

3.3 Significant Factors in DPMO

Significant factors were determined by evaluating the effect of each input variable on the response variable defect rate (DPMO). The impact or effect of each variable is the measured response on the defect rate when the level of each input variable is individually changed. This is used to measure the sensitivity of the net prediction to changes in the independent variables. The lower the impact, the less of an effect that an individual variable has on the net prediction. It should also be noted that the impact values calculated are only true for a given model and may change as the model is altered. To determine whether or not the impact is statistically significant is tested by calculating the p-values while testing the hypothesis that:

$$H_0: \mu_{s+} - \mu_{s-} = 0 \tag{15}$$

$$H_1: \mu_{s+} - \mu_{s-} \neq 0 \tag{16}$$

The impact of the variable is simply the difference between the averages of the high and low with a larger difference indicating a more significant impact. The values were compared against a standardized range and the values were given a positive 1 or negative 1 depending on whether they fell above or below the mean value. The difference between the high and the low values were then used to determine the impact of the individual variables on the response variable.

	Engage. length	Conn. width	Conn. height	Female Pigtail	Male Pigtail	Work Height
Conn. 1	-1	-1	-1	1	-1	1
Conn. 2	1	-1	-1	1	-1	1
Conn. 3	-1	-1	-1	1	-1	-1
Conn. 4	-1	-1	-1	-1	1	-1
Conn. 5	-1	-1	-1	-1	1	1
Conn. 6	1	-1	1	-1	1	-1
Conn. 7	-1	1	-1	1	-1	-1
Conn. 8	-1	1	-1	-1	1	-1
Conn. 9	1	1	1	-1	1	-1
Avg(+)	479	78	371	590	557	854
Avg(-)	618	818	629	557	590	430
Impact Effect	-139	-740	-259	33	-33	424

Table 5: Best subsets input variables impact factors

From the table above, the impact of each variable in the best subsets regression model can be plotted to better illustrate the response resulting from the change in a particular variable.

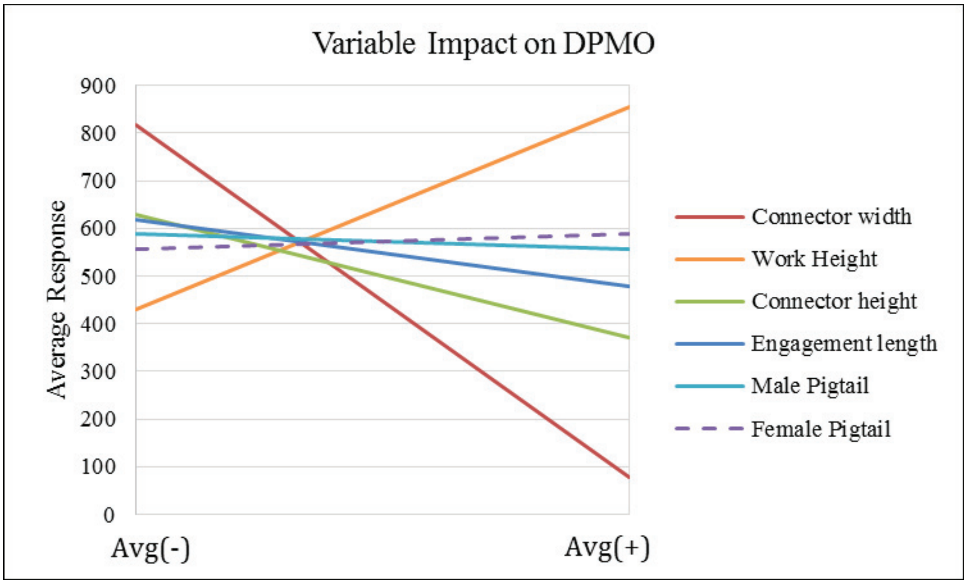

Figure 5: Impact effects of variables on defect rate

From Figure 5, it can be seen that the most significant impact for a variable in the best subsets model occurs from varying the connector width of the electrical connector and that there appears to be a reduction in the response variable or defect rate (DPMO) while increasing the width.

The impact variables from most significant to least significant:

- Connector width
- Work height

- Connector height
- Engagement length
- Male pigtail
- Female pigtail

3.4 Application in Automotive Assembly

A pilot study was proposed to test the results of the best subsets regression model and to further conclude the validity of the generated model. The variable pigtail length was selected from the six variables included in the final model due to it having the highest impact that did not necessitate a very significant design or fixturing change. The limitation on significant change was imposed so as to not disrupt the current scheduled production flow. A trial of the lengthened electrical connector was proposed to compare predicted vs actual defect rate. A connector with a high defect, short lead time, and ease of change without disrupting scheduled production was desired and the best candidate was the front door map pocket ambient lighting connector that is located inside the front left hand side door panel. The connector can be seen in Figure 6 below.

During assembly, the inner door wiring harness is clipped in place onto the inner door panel by a line associate before being connected to the main door wiring harness and then attached to the outer door panel. The inner door harness typically connects devices such as door lights, switches, and safety features to the main harness and is readily used by the vehicle occupants. Once connected to the main door harness on outer door panel, the inner door panel is clipped in place onto the outer door panel. If a connector is not properly seated during assembly, potential electrical defects will show in subsequent vehicle testing stations and result in the need for costly rework and disassembly of the door panel to determine the root cause. Vehicle electrical connections undergo significant testing with each function being tested before a vehicle is allowed to continue. Door assemblies for many manufacturers are typically tested using continuity tests, human use of switches, and manufacturer specific computerized testing. These connections are tested at multiple points during the assembly process to ensure the overall vehicle quality before leaving the manufacturer.

During the course of the trial of the door wiring harness, it was found that during the connection of the inner door harness to the main door harness, the cable going from a branch point to the electrical connector in question had the potential to be pulled with a large amount of force. This pulling force creates the possibility for the connector to be pulled out creating an electrical connector defect. To account for this potential, a lengthened pigtail as described by the proposed model was used to prevent the possibility of a defect occurring. In Figure 6(b), the lengthened pigtail highlighted allows for the majority of potential defect creating force to be placed on the clips holding the wiring harness rather than the electrical connector. An extended trial is currently being conducted to determine the changes effect on the DPMO of the door harness connector during production as an evaluation of the final regression model ability.

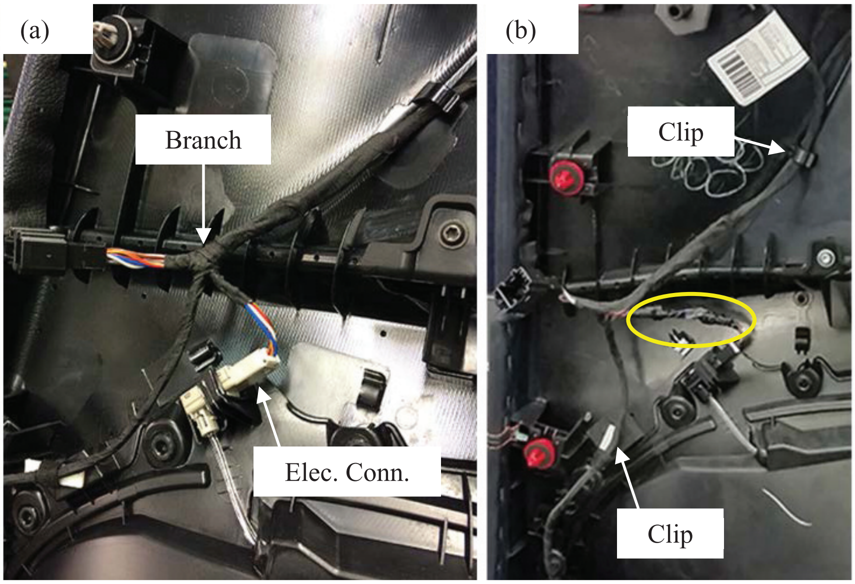

Figure 6: (a) Front door wiring harness prior to improvement; (b) Front door wiring harness post change, length change circled

4 Conclusion

Continuously changing and more complex products demanded by consumers are increasing the focus towards quality in the automotive industry. This is especially true as vehicle assembly comprises such a large portion of the total cost and manufacturing time in the automotive industry making defect prediction and elimination imperative.

Based on the Antani model and applied to a fully manual automotive assembly process, the design, process, and human factors complexity model was derived to predict the defect rates of automotive electrical connectors. 41 variables were analyzed to understand how the correlation of each with defect rate and to distinguish the relationships that are occurring within the model. OLS regression techniques were applied to create a general regression model that included all 41 variables and resulted in an R-squared value of 0.576. Best subsets regression modeling was then used to simplify the general regression model and resulted in a model that was reduced to 6 variables, greatly reducing the data collection requirements, while increasing the R-squared to 0.923. To build a comprehensive understanding of the defect prediction model and its variables, the significant impactors of the best subsets regression model were examined and ranked from most to least significant impact on defect rate.

To validate the model, a demonstration is underway and applied to an automotive door assembly production line by predicting the defect rate of a door wiring harness prior to and after a modification. A potential for defects was found and eliminated that matched the proposed significant impact variables for automotive electrical connectors and the change is being trialed for production release.

The methodology proposed by Antani and used in this research was previously validated for fully-automated and semi-automated automotive assembly. These research efforts have shown that the methodology and model applied to a fully-manual automotive assembly process can be shown as a robust and comprehensive measure and correlation of manufacturing complexity and resulting product quality for the global automotive industry.

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